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Proof of concept experiment to demonstrate the efficacy of the 'Smart Tuna Hook'

Report prepared for AHI Enterprises

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Introduction

Each year many thousands of seabirds are accidentally killed on longline hooks when birds, attracted to fishing vessels by discards and baits, ingest baited hooks and subsequently drown (Anderson et al. 2011; Baker et al. 2002). While most mortality occurs directly when birds are caught during line-setting and, less commonly, hauling, seabirds may also die after they are released with critical injuries, or through ingestion of fishing hooks when birds eat discarded baits and fish heads containing hooks.

The level of longline-related mortality is such that longline fishing has been identified as a major threat affecting many seabirds (Anderson et al 2011; Gales 1998; Baker and Wise 2005), causing widespread declines in populations throughout the world (Alexander et al. 1997; Birdlife International 1995; Croxall 1998; Delord et al. 2005; Gales 1998; Poncet et al. 2006; Tuck et al. 2001). Most of the larger albatrosses and petrels that breed and forage within the southern hemisphere are threatened by longline fishing (Gales 1998).

A range of mitigation measures for reducing the incidental catch of seabirds in longline fisheries have been developed (Brothers et al. 1999; Dietrich et al. 2004; Bull 2007; Lokkeborg 2008, 2011) that can be employed according to circumstance. While considerable progress has been made in mitigating bycatch in demersal longline fisheries (e.g. Moreno et al. 2007), principally through the development of effective bird scaring lines (Melvin 2003; Melvin et al. 2004), Integrated Weight Line in autoline systems (Robertson et al. 2006), night setting and seasonal closures (SC-CAMLR 2005), proven and accepted seabird avoidance measures in pelagic fisheries require substantial improvement. In 2007, ACAP's Seabird By-catch Working Group reviewed available research on seabird by-catch mitigation measures for pelagic longline fishing (ACAP Seabird Bycatch Working Group 2007; also see Melvin and Baker 2006). They concluded that night setting is currently the only mitigation measure proven to be widely effective with pelagic longline gear, but its widespread adoption is constrained because it is considered to reduce operational efficiency when targeting some pelagic fish species.

In an attempt to address this situation an Australian company, AHI Enterprises, has been working on the development of a mitigation device that will significantly reduce seabird bycatch in pelagic longline fisheries in particular, but will also have utility in other longline gear types. Resulting from this work is a device that is known as the Smart Tuna Hook System. The system uses a modified tuna long-line hook, circle or Japanese style, which accepts a specially designed shield that disarms the hook once it has been baited. The steel shield, once attached to the baited hook, creates a large 3 dimensional barrier encompassing the hook's point and barb, which prevents ingestion and making it impossible for any seabird or turtle to be hooked, internally or externally. The shield is easily and quickly snapped and held onto the baited hook by a clip that has a corrodible alloy link. The link causes the shield to be released within 15 minutes after the hook has been immersed in salt water, allowing fish to be caught after the baited hook has passed beyond the normal diving and feeding depths of most seabirds. After release from the hook the shield sinks to the seafloor where it corrodes within 12 months, leaving no pollution or toxic residue. The byproduct is iron oxide and carbon.

The smart tuna hook works to reduce seabird bycatch in two ways:

1. It adds weight to each branchline directly at the hook, thus increasing sink rate and reducing the availability of baited hooks to seabirds. The mild steel shield is hydrodynamic, weighs approximately 38gms and once attached increases the sink rate of the baited hook to 0.6 metres per second

(B.Baker and G.Robertson, unpublished). Unlike weighted swivels or fixed weights, however, the weight is not present at the time of hauling because the shield has been released during the soak time. This addresses the safety concerns of many fishers that weights applied to gear can potentially injure crew members in 'bite-off' or break off situations during gear retrieval (Sullivan et al 2012).

2. The shield protects the hook from injuring or being ingested by seabirds in the event that diving birds manage to seize a baited hook during deployment.

The Smart Tuna Hook presents other operational advantages to fishers that will encourage uptake if the environmental benefits can be demonstrated by the experimental work. Firstly, lead loss to the marine environment from lost fishing gear will be reduced, benefitting fishers in a reduction in costs and an increase in crew safety. Secondly, bait loss during the setting process will be significantly reduced through minimised seabird attacks following improved hook sink rates. Bait loss is known to be as high as 15% in pelagic fisheries, and the shield will also act to protect the bait from tearing off the hook when it enters the water after being cast from the vessel.

Successful pilot studies of the STH in the Coral Sea, Australia, have shown the system is operationally effective and had no impact on efficient setting of gear (Jusseit 2010). Limited ocean seabird testing undertaken in Kaikoura, New Zealand, indicated that use of the Smart Tuna Hook was a significant deterrent to seabirds attacking baits. However, support and feedback from stakeholders indicates a larger trial under experimental conditions is warranted and justified before uptake and the device is put into full commercial production.

In 2013 Latitude 42 Environmental Consultants Pty Ltd were engaged by AHI Enterprises to conduct an at sea trial/experiment setting Smart Tuna Hooks and shields to demonstrate the efficacy of this measure in reducing seabird bycatch whilst maintaining catch of target species. The experimental work was conducted on pelagic longline vessels targeting tuna and swordfish out of Cape Town, South Africa during the Austral spring of 2014. In this paper we report on this experiment and the effectiveness of the Smart Tuna Hook in mitigating capture of seabirds while maintaining or improving capture of target species.

Methods

General

Field work to test the efficacy of the 'Smart Hook' System was carried out between July-October 2014 off the coast of South Africa, a well-known seabird 'hotspot' that is readily accessible for both seabird observation and research work. Twenty four species of albatrosses and petrels have been recorded foraging in South African waters (Petersen et al., 2009), and bycatch rates in the South African Pelagic Longline Fishery are known to be high. Baker et al (2007) assessed this fishery to be a very high impact fishery for seabirds with >1000 seabirds killed in the fishery each year. Fishing effort is divided between domestic vessels that primarily target broadbill swordfish (*Xiphias gladius*), and foreign (Japanese, Korean, Taiwanese) fishing vessels that usually set their gear deeper and target albacore (*Thunnus alalunga*), yellowfin (*T. albacares*) and bigeye tuna (*T. obesus*) (Cooper and Ryan, 2002). Effort is usually concentrated along the edge of the continental shelf although some vessels fish farther offshore in the Atlantic and Indian Oceans, outside the South African EEZ (Cooper and Ryan, 2002). More detailed descriptions of the fishery are provided in Baker et al (2007) and Melvin et al (2013).

The experiment involved a direct comparison of the Smart Tuna Hook and conventional pelagic hooks in pelagic fishing operations. The experiment primarily focussed on the efficacy of mitigating seabird by-catch using the Smart Hook in temperate waters, but data were also recorded on catch of target species and interactions with other non-target species.

Fishing vessels and gear

The experiment was conducted on two fishing vessels, the *FV Seawin Emerald* and *FV Seawin Diamond*. Both these vessels are 25-m steel hulled longliners operating out of Cape Town, South Africa. Gear configuration and operational procedures during fishing were similar for both vessels. They set a 3.2mm monofilament mainline without a line shooter. The mainline was suspended on floats on 17m long droppers. Branch lines were made of 1.8mm monofilament nylon, 13.4 m long and were fitted with a mix of #14/0 J hooks and circle hooks. Baited hooks were deployed to the outer edge of vessel wake on both sides of the vessel. The bait was whole Argentine short-fin squid (*Illex argentinus*). All baits were dead. Branch lines with squid bait were always accompanied by a green light stick placed 2m from hooks. A typical set on each vessel involved deploying 900–1500 hooks at 8 knots vessel speed with 4 branch lines between floats and branch lines 50m apart. Branch lines were set from gear bins every 8 s off both sides of the vessel. Radio beacons were deployed at 130 branch line intervals. The main species targeted in the experiments were broad-bill swordfish (*Xiphias gladius*), yellow-fin tuna (*Thunnus albacores*) and big-eye tuna (*T. obesus*). Time-of-day of line setting varied with moon phase and operational issues, but in general commenced at nautical dusk as swordfish was the main target species. All sets of experimental gear occurred during the night.

This experiment was conducted over three fishing trips and 28 longline sets. The experiment consisted of a comparison of a) conventional surface setting of pelagic long-lines from the stern of a vessel using hooks employing a form of conventional mitigation regulated by the jurisdiction within which the experiment was undertaken but without the 'Smart Hook' shield (the 'conventional method' or control), and b) the same gear as described for the control but with the 'Smart Tuna Hook' shield fitted to each hook ('Smart Tuna Hook method' or STH). The regulated mitigation regime used in the control consisted of placement of an 80 g weighted swivel placed 3.2 m from each hook. In addition, all hooks for the both the control and STH were set at night. Currently, pelagic long-line vessels worldwide set gear using mainly method 'a'. It was originally intended to place the Smart Tuna Hook shield on hooks fixed to branchlines without weighted swivels, but the crew were unwilling to use unweighted branchlines in experimental work, and the conventional and STH methods therefore differed only in the presence or absence of Smart Tuna Hook shields. The experiment sought to examine the capacity of the two hooking methods to deter seabird species known to be readily interact with pelagic long-line fishing gear, particularly albatrosses, white-chinned petrels and shearwaters. The response variable was the capture of seabirds and the capture of target fish species. Because of concerns of statistical power, work was undertaken using a 1 X 2 factorial approach:

Factors	**Treatments**	
1. Bait Type	<u>Squid</u>	
2. Hook method	No Smart Hook Shield	Use of smart hook shield

Both treatments were tested during each longline set to eliminate the potentially confounding effect of 'set'. Both treatments were tested in a block (experimental set) of c.120-150 hooks for each treatment on the longline, with a length of c.500m of mainline to isolate each treatment in the set and ensure a degree of independence between treatments. The number of hooks set in each block differed in each block and was set to suit the normal operations of the vessel with respect to total hooks set, in order to ensure that evaluation of each treatment was balanced. For example, if the vessel was intending to set 1500 hooks per set, each block for that set was standardised at 150 hooks, so that 10 blocks, or five paired blocks, could potentially be set each day. The setting order of treatments during each set was randomised.

Statistical models and methods

The response variables modelled for each of control hooks and Smart Tuna Hooks (STHs) in each pair of deployments were (a) the number of seabirds caught (i.e. tallied across the 3 species of black-browed albatross, shy albatross, and white-chinned petrel); (b) number of fish totalled across the 5 main commercial species caught; and (c) the number of fish for each of the 5 main commercial species caught of albacore tuna (ALB), yellowfin tuna (YFT), bigeye tuna (BET), southern bluefin tuna (SBF), and swordfish (SWO). The response variables were modelled using generalized linear mixed models (GLMMs) (Bolker et al. 2009) using a Poisson error distribution and the log of number of hooks within each hook type within each pair as an offset. The linear predictor included just the single factor of hook type (**`Treat_f`**) (i.e. control vs STH). For the GLMM random effects of pair within trip (**`Pair_f`**) and trip number (**`TripNr_f`**) were included in the conditional linear predictor. The GLMM was fitted using `glmer` (Bates et al., 2014) function in the `lme4` library in R (R Core Team, 2013) where this function evaluates the marginal likelihood by approximation of the integral of the conditional likelihood across the assumed Gaussian distributions for random effects. Robertson et al. (2006) modelled seabird bycatch in paired deployments of two line types in the demersal ling fishery on the west coast of New Zealand using a similar Poisson GLMM except that Penalized Quasi-likelihood Estimation (PQL) (Schall, 1991; Breslow and Clayton, 1993) was used for estimation. Marginal likelihood though more numerically intensive has superior estimation properties to PQL in some situations but is always at least as good as PQL. Irrespective of this the response variable of total seabird bycatch had a large proportion of zeros for with only 2 out of 63 STH pair deployments being non-zero and only 9 out of 63 control pair deployments being non-zero. However, the Poisson distribution, even with a very low expected value for rate of the order of 0.19 per 150 hooks (see results for controls in Appendix 1 `MCMCglmm` output) (where the average number of hooks per STH or control deployment had a range of 75 to 150 with median of 150 and mean of 139.3) has difficulty modelling such a large proportion of zeros. For this reason we applied a zero-inflated Poisson (ZIP) distribution model which is not a standard GLM and cannot be fitted using `glmer`. Further, the response variables of number of fish caught for each commercial species also contained a high proportion of zeros of the order of 50%.

So in order to incorporate random effects in the ZIP model, the `MCMCglmm` function in the `MCMCglmm` R-library (Hadfield, 2010) that applies Markov Chain Monte Carlo sampling (Gilks et al., 1996) was employed for these response variables. The offset of log of number of hooks was included in `MCMCglmm` for the "trait" of the Poisson latent component (Hadfield, 2014) by setting a regression parameter associated with the variable log of number of hooks with prior Gaussian distribution with mu of 1.0 and variance of 1e-9. Other parameters were given diffuse priors (Hadfield, 2010).

For both `glmer` and `MCMCglmm` the output parameters of rate of seabird bycatch per hook and fish catch per hook for each of control and STH deployments were parameterized as a single parameter of the percent reduction in bycatch rate (for seabirds) and catch rate (for fish) of the STH relative to the control deployments (R) (i.e. this definition does not preclude an increase in catch rate in which case this parameter would have a negative estimate). Using `glmer` output (see Appendix 1) and using the parameter defining catch rate on the log scale for STH minus that for the control, of $\hat{\tau}$ then $\hat{R} = 100 \left[1 - \exp\{\hat{\tau}\}\right]$ (See Appendix for glmer output), the fixed effect parameter "`Treat-fCap`" is equivalent to $\hat{\tau}$. Approximate 95% confidence intervals were obtained for $\hat{R}$

using `glmer` with lower limit of $100\ (1 - \exp\{\hat{\tau} + 2se\ (\hat{\tau})\}$ and upper limit of $100\ (1 - \exp\{\hat{\tau} - 2se\ (\hat{\tau})\}$. In contrast using the `MCMCglmm` output (see Appendix 1), MCMC sample values for (by)catch rate per hook for each of STH (α_{STH}) and control (α_{con}) deployments was obtained. The estimate of R was taken as the median of the sample of values with *i*th sample value of $R_i = 100\left(\hat{\alpha}_{con,i} - \hat{\alpha}_{STH,i}\right) / \hat{\alpha}_{con,i}$. Confidence bounds with 95% support were obtained as 2.5% and 97.5% quantiles of the set of sample values of R. Two MCMC estimations were carried out for the total seabird bycatch, one with 1,000 sample size using a burn-in sample of 200,000, total sample of 700,000, and thinning rate of 1 in 500. The second MCMC with the thinning rate dropped to 1 in 250 to give a final sample of 2,000. The fish catch for each commercial fish species use the first of these two MCMC sampling strategies since the samples were better behaved presumably because of a less extreme number of excess zeros.

Results

General

Gear loss was minimal for most sets, but significant sections of the treatments C2Cap, C2 Con, H1Cap, H2Cap, and H3Con were lost when multiple line breaks lead to complete loss of gear.

Seabird bycatch was high and a total of 13 birds were caught across the three trips. Eleven of these birds were caught on the control treatments and 2 birds on the STH treatments. All birds caught had either been hooked through the beak or mouth. The two birds caught on the STH treatments had been hooked through the throat just below the beak. The one White-chinned Petrel that was caught on the STH treatment came up tangled in line and was effectively attached to the mainline, indicating a fault during the setting process, potentially because the STH was deployed with a weighted swivel on the branchline as well as the weight of the STH at the hook, and the weights fell either side of the mainline on casting, hence encouraging a tangle.

Seabird catch

Two sets of analysis were carried out for total seabird bycatch. The first set used all the data. The second set dropped the pair 3J1, both control and STH values, since a single WCP was caught on the STH but this was considered potentially unrepresentative due to a faulty deployment of the STH that caught the bird (see discussion). The Trip random effect (**`TripNr_f`**) was estimated to have zero variance by `glmer` so subsequently the only random effect incorporated in `glmer` and `MCMCglmm` was (**`Pair_f`**).

Table 1 gives the results of the fit of the Poisson GLMM and ZIP models in terms of the estimates of R and its approximate 95% confidence bounds for total seabird bycatch. Seabird bycatch rate was estimated to range from 0.647 — 1.411 birds/1000 hooks for the control hooks, and 0.059 — 0.247 birds/1000 hooks for STH (Table 1). The estimated average reduction in bycatch when using the STH was significantly lower when compared with the control, and ranged from 82-91% reduction, depending on the model used and the dataset fitted (Table 1). Dropping pair 3j1 from the analysis increased the average reduction slightly, but dramatically increased the lower confidence bound by around 30 percentage points (Table 1).

It should be noted that due to the very high proportion of zeros in the seabird bycatch data, less confidence should be placed in the GLMM results that used a Poisson error distribution compared to the ZIP model combined with MCMC sampling in which this feature of the data is more realistically modelled.

Appendix 1 gives `glmer` and `MCMCglmm` function calls and associated R commands as well as selected outputs from both functions for the full dataset and 1,000 final MCMC samples.

Fish catch

Table 2 gives the results of the fit of the Poisson GLMM and ZIP models in terms of the estimates of R and its approximate 95% confidence bounds for total commercial fish catch and individual-species of commercial and non-commercial fish catch. There was no detectable difference between setting methods in the catch rates of swordfish, yellow-fin tuna, big-eye tuna, southern Bluefin tuna, albacore tuna and other commercially valuable species (Table 2). A zero value for the percent reduction was always well within the 95% confidence bounds, indicating no detectable detrimental effect on fish catch for any species.

Only with albacore was there any indication that there could be a difference in catch between the control and the Smart Tuna Hook, but the confidence levels for the estimated difference are quite broad and include zero, meaning that the difference could be due to chance alone.

Appendix 1 gives `glmer` function call and associated R commands as well as selected outputs for total commercial fish catch and output and graphs of MCMC samples for yellowfin tuna as a typical example of all 5 commercial species.

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Table 1. **Percent reduction (*R*) in rate of seabird bycatch for Smart Tuna Hooks (STH) compared to control hook deployments, and bycatch rate for control hooks and STH estimated using each of Poisson GLMM, and zero-inflated Poisson MCMC sampling**

Estimation Model	**Dataset**	**Percent Reduction (*R*)**	**Confidence Limits for *R* (~95% level)**	**Bycatch Rate (seabirds per 1000 hooks) (~95% Confidence Limits)**	
				Control	**Smart Tuna**
GLMM	All 63 pairs	81.82	15.43, 96.09	0.730 (0.211, 2.531)	0.133 (0.223, 0.790)
	Drop 3J1 pair	90.91	26.58, 98.87	0.647 (0.163, 2.561)	0.059 (0.006, 0.617)
MCMC (1000 samples)	All 63 pairs	83.47	36.45, 97.60	1.241 (0.668, 2.203)	0.198 (0.029, 0.697)
	Drop 3J1 pair	91.39	72.50, 98.61	1.304 (0.648, 2.348)	0.110 (0.018, 0.460)
MCMC (2000 samples)	All 63 pairs	82.57	20.91, 95.36	1.411 (0.598, 2.338)	0.247 (0.062, 0.844)
	Drop 3J1 pair	85.76	49.70, 98.19	1.310 (0.672, 2.101)	0.181 (0.027, 0.542)

Table 2. Percent reduction (positive) or increase (negative) in rate of commercial and non-commercial species catch for Smart Tuna Hooks (STH) compared to control hook deployments estimated using Poisson GLMM, and zero-inflated Poisson MCMC sampling and catch numbers by hook type

Response Variable	Method	Percent Reduction (+) or Increase (-)	Confidence Limits (~95% level)	Total Number Caught Control	Total Number Caught STH	Number of zero catches (out of 126 sets within pairs)
Total all commercial species	**GLMM**	**6.95**	**-6.45, 18.67**	**446**	**415**	**12**
albacore tuna	MCMC	31.60	-24.63, 61.01	124	97	60
yellowfin tuna	MCMC	11.04	-58.26, 49.22	143	142	58
bigeye tuna	MCMC	-0.57	-88.56, 47.67	99	93	65
southern bluefin tuna	MCMC	-4.28	-75.18, 39.43	23	25	88
swordfish	MCMC	-10.62	-100.13, 31.25	57	58	64
Total all non-commercial species	**GLMM**	**-2.02**	**-9.58, 5.02**	**536**	**1567**	**4**
Atlantic pomfret (POA)	MCMC	26.38	-1537.38, 98.65	14	45	119
Short-finned mako shark	MCMC	9.10	-54.86, 42.00	112	106	46
blue shark	MCMC	1.31	-33.48, 27.45	1410	1416	5

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Discussion

We were able to demonstrate that the use of the Smart Tuna Hook led to a reduction in the bycatch of seabirds of between 81.8% – 91.4% in one of the highest-risk fisheries to seabirds in the world (Anderson et al. 2011; Petersen et al 2009). In a fishery where the bycatch rate of seabirds exceeded 1 bird/1000 hooks (this study), and where the capture of more than 25 birds by a vessel each season leads to a suspension of fishing activity for that vessel, the Smart Tuna Hook offers an feasible option for pelagic fishers to significantly reduce the level of interactions with seabirds and hence remain active in the fishery. It clearly provided a significant deterrent to seabirds attacking baits.

While some forms of seabird bycatch mitigation are thought by fishers to impact the catch of commercial target species, in our study there was no detectable difference between setting methods in the catch rates of swordfish, yellow-fin tuna, big-eye tuna, southern Bluefin tuna, albacore tuna and other commercially valuable species, indicating no detectable detrimental effect on fish catch for any species. This provides confidence for fishers planning to use the Smart Tuna Hook that in looking to reduce the risk of seabird bycatch their commercial operations will not be negatively impacted. It stands to reason that if seabirds cannot readily access baited hooks because of the protection provided by the STH shield, then bait retention will be improved and the probability of catch of target species enhanced. There is some indication of this from previous work carried out in the Coral Sea, Australia (Jusseitt 2010) but statistical demonstration of this would likely require examination of many thousands of hooks under controlled experimental conditions. However, there would appear to be immediate economic benefits to the South African Pelagic Longline Fishery of using the STH and minimising seabird bycatch, thus greatly reducing the risk of a seasonal closures to individual vessels and subsequent loss of income.

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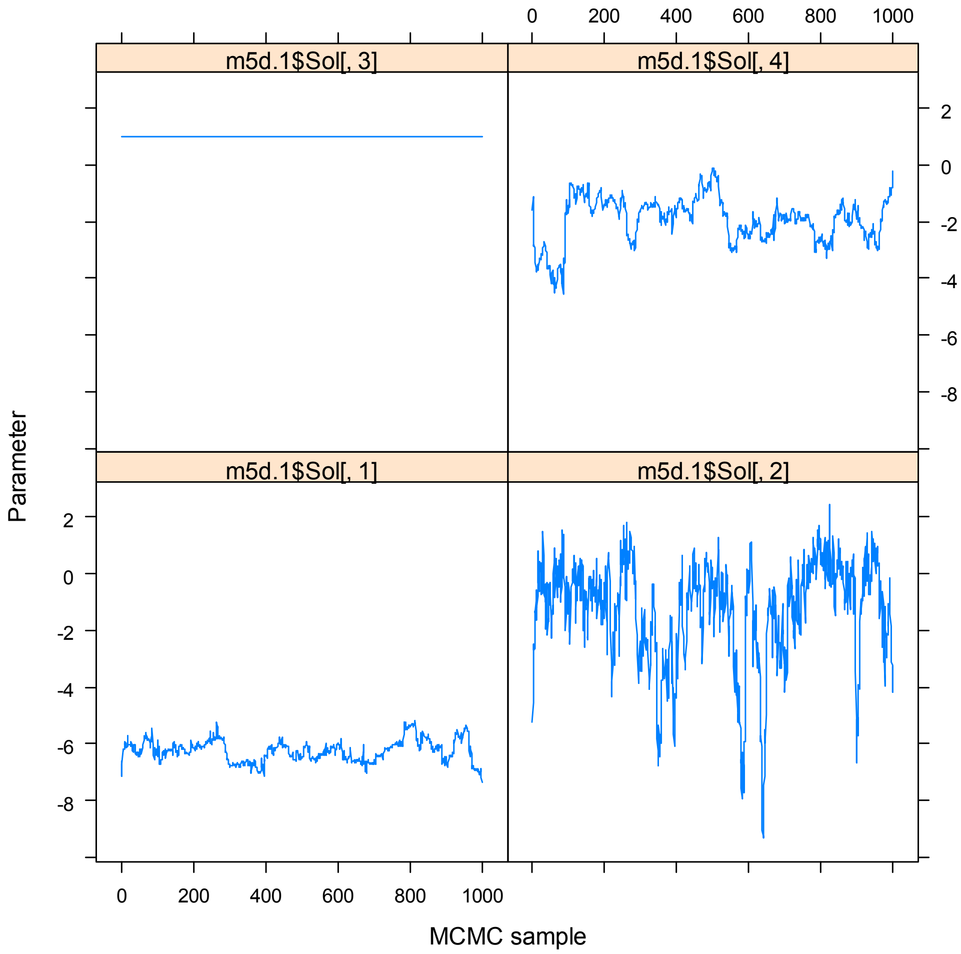
Appendix 1

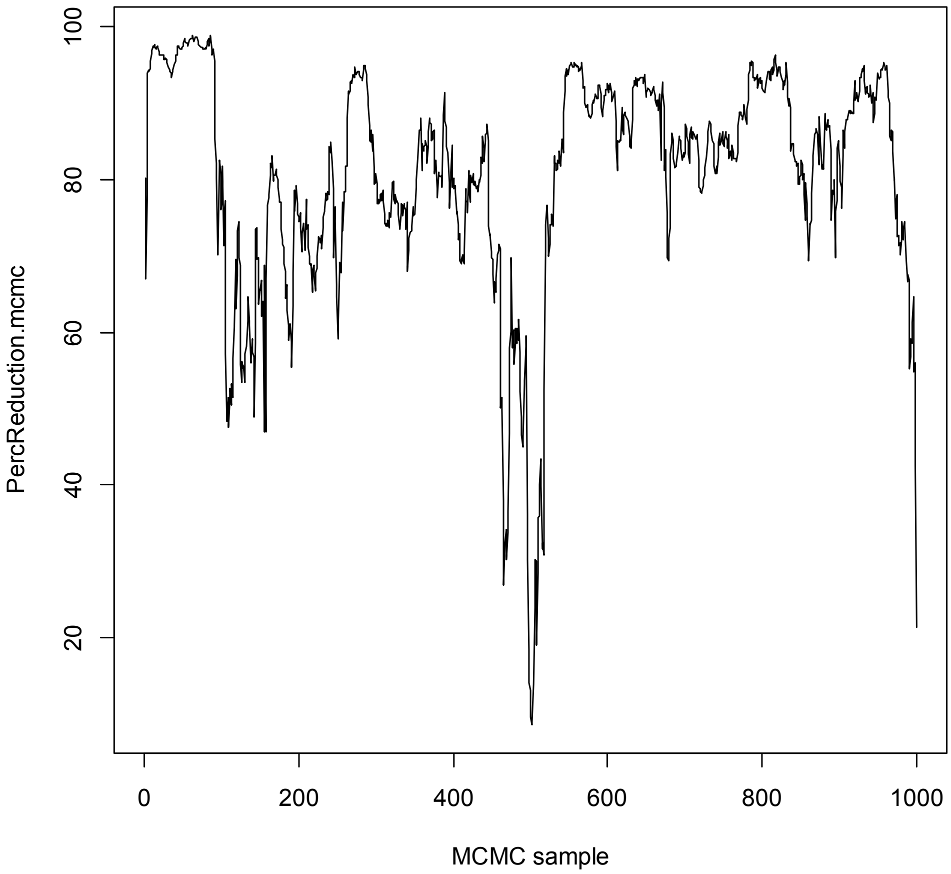
```
> summary(data)
    RecordNr          TripNr          SetNr           Pair_ID    Setting_Method     Vessel
Bait         Hooks           BB_Alb            Shy_Alb
 Min.   :  1.00   Min.   :1.000   Min.   : 1.00   1A1Cap :  1   Control:63     Min.   :1.000
squid:126   Min.   : 75.0   Min.   :0.000000   Min.   :0.00000
 1st Qu.: 32.25   1st Qu.:2.000   1st Qu.:10.00   1A1Con :  1   STH    :63     1st Qu.:1.000
1st Qu.:129.2   1st Qu.:0.000000   1st Qu.:0.00000
 Median : 63.50   Median :3.000   Median :17.00   1B1Cap :  1                  Median :2.000
Median :150.0   Median :0.000000   Median :0.00000
 Mean   : 63.50   Mean   :2.286   Mean   :16.29   1B1Con :  1                  Mean   :1.524
Mean   :139.3   Mean   :0.007937   Mean   :0.06349
 3rd Qu.: 94.75   3rd Qu.:3.000   3rd Qu.:23.00   1B2Cap :  1                  3rd Qu.:2.000
3rd Qu.:150.0   3rd Qu.:0.000000   3rd Qu.:0.00000
 Max.   :126.00   Max.   :3.000   Max.   :28.00   1B2Con :  1                  Max.   :2.000
Max.   :150.0   Max.   :1.000000   Max.   :2.00000

      WCP           Total_birds
Min.   :0.00000   Min.   :0.0000
1st Qu.:0.00000   1st Qu.:0.0000
Median :0.00000   Median :0.0000
Mean   :0.03175   Mean   :0.1032
3rd Qu.:0.00000   3rd Qu.:0.0000
Max.   :1.00000   Max.   :2.0000

> Nd <- dim(data)[1]
> Ndd <- Nd/2
> data$Treat_f <- factor(x=rep(seq(2,1,-1),times=Ndd), levels=c(1,2),
labels=c("Con","Cap"))
> data$Pair_f <- factor(x=rep(c(1:Ndd),each=2), levels=c(1:Ndd))
> data$TripNr_f <- as.factor(data$TripNr)
> data$Lhooks <- log(data$Hooks)
>
> ### total seabird bycatch  ###
>
> ### Poisson GLMM using glmer()
>
> glmer.01 <- glmer(formula=Total_birds ~ 1 + Treat_f + (1|Pair_f), offset=Lhooks,
data=data, family=poisson)
> summary(glmer.01)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: poisson  ( log )
Formula: Total_birds ~ 1 + Treat_f + (1 | Pair_f)
   Data: data
 Offset: Lhooks

     AIC      BIC   logLik deviance df.resid
    85.0     93.5    -39.5     79.0      123

Scaled residuals:
    Min      1Q  Median      3Q     Max
-0.5020 -0.2982 -0.1680 -0.1247  4.4577

Random effects:
 Groups Name        Variance Std.Dev.
 Pair_f (Intercept) 1.187    1.089
Number of obs: 126, groups:  Pair_f, 63

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -7.2223     0.6215 -11.621   <2e-16 ***
Treat_fCap   -1.7047     0.7686  -2.218   0.0265 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
           (Intr)
Treat_fCap -0.190
>
> exp(fixef(glmer.01)[2])
Treat_fCap
```

```
 0.1818178
> vcov(glmer.01)
2 x 2 Matrix of class "dpoMatrix"
            (Intercept)  Treat_fCap
(Intercept)  0.38626842 -0.09087409
Treat_fCap  -0.09087409  0.59068291
> se.teff <- (vcov(glmer.01)[2,2])^0.5
> print(c(fixef(glmer.01)[2],se.teff))
Treat_fCap
 -1.704750   0.768559
> PercReduction <- 100*(1-exp(fixef(glmer.01)[2]))
> sum(fixef(glmer.01))
[1] -8.927003
>
> PercReduction.L1 <- 100*(1-exp(fixef(glmer.01)[2]+2*se.teff))
> PercReduction.L2 <- 100*(1-exp(fixef(glmer.01)[2]-2*se.teff))
>
> print(c(PercReduction,PercReduction.L1,PercReduction.L2))
Treat_fCap Treat_fCap Treat_fCap
  81.81822   15.43350   96.09092

> ### ZIP using MCMCglmm ###

> data$Treat <- as.integer(data$Treat_f %in% "Cap")
>

> prior1 <- list(R = list(V = diag(2), nu = 0.002, fix = 2), B= list (mu =
matrix(c(0,0,1,-1.7),4),V = diag(4)*(10)))
> diag(prior1$B$V)[3]<-1e-9
>
>
> m5d.1 <- MCMCglmm(Total_birds ~ trait - 1 + at.level(trait,1):Lhooks +
at.level(trait,1):Treat, rcov = ~idh(trait):units, data = data,
+      nitt=700000, thin=500, burnin=200000, prior = prior1, family = "zipoisson",
verbose = FALSE)
>
> summary(m5d.1)

 Iterations = 200001:699501
 Thinning interval  = 500
 Sample size  = 1000

 DIC: 81.22326

 R-structure:  ~idh(trait):units

                     post.mean  l-95% CI  u-95% CI eff.samp
Total_birds.units     0.006042 0.0001553  0.02126    503.8
zi_Total_birds.units  1.000000 1.0000000  1.00000      0.0

 Location effects: Total_birds ~ trait - 1 + at.level(trait, 1):Lhooks +
at.level(trait, 1):Treat

                          post.mean l-95% CI u-95% CI eff.samp  pMCMC
traitTotal_birds            -6.2435  -6.9971  -5.4590    18.11 <0.001 ***
traitzi_Total_birds         -1.2936  -5.2971   1.7077    34.23  0.504
at.level(trait, 1):Lhooks    1.0000   0.9999   1.0001  1000.00 <0.001 ***
at.level(trait, 1):Treat    -1.9230  -3.6237  -0.3581    11.86 <0.001 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
>
> x <- seq(1,1000)
> xyplot(m5d.1$Sol[, 1]+m5d.1$Sol[, 2]+m5d.1$Sol[, 3] + m5d.1$Sol[, 4] ~ x,
outer=TRUE, type="l", xlab="MCMC sample")
> savePlot(filename = "Models Pars MCMC.emf", type ="emf")
>
> xyplot(m5d.1$Sol[, 1]+m5d.1$Sol[, 2]+m5d.1$Sol[, 3] + m5d.1$Sol[, 4] ~ x,
outer=TRUE, type="l", ylab="Parameter",
+   xlab="MCMC sample")
> savePlot(filename = "Models Pars MCMC.emf", type ="emf")
>
> summary(m5d.1$Sol[,1])
```

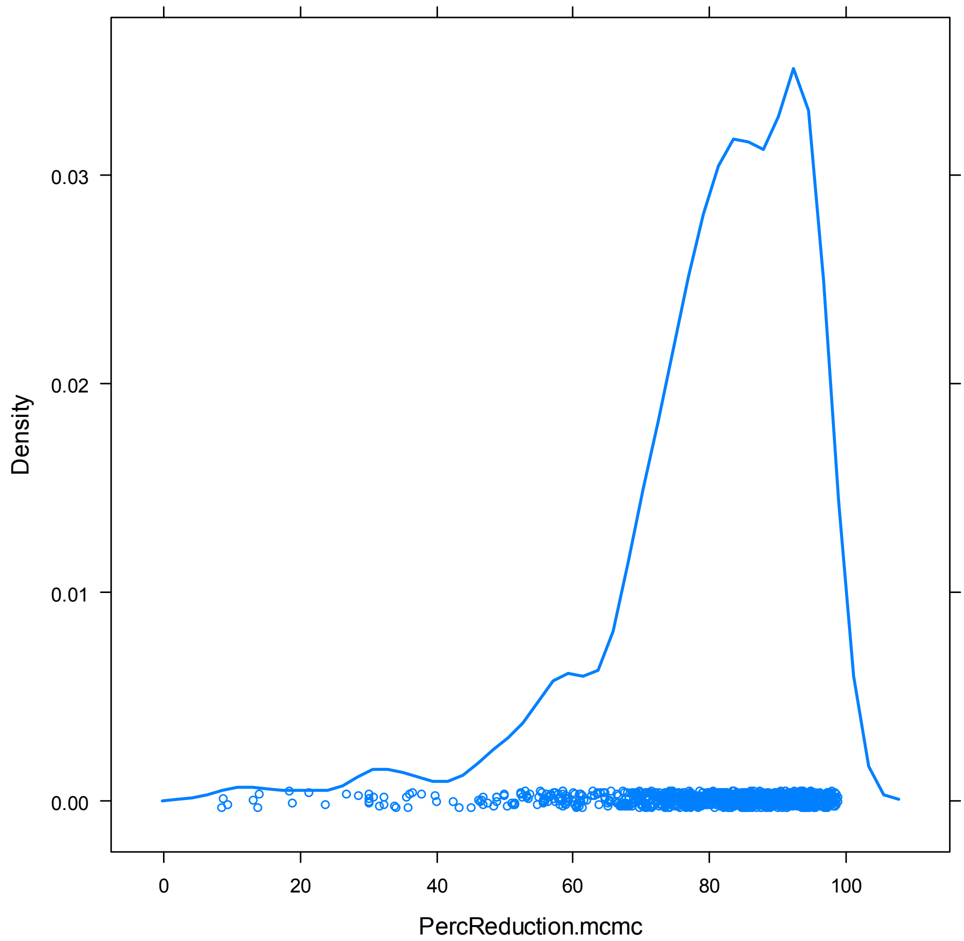
```
Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
      -6.24345        0.38369        0.01213        0.09016

2. Quantiles for each variable:

  2.5%    25%    50%    75%  97.5%
-6.960 -6.535 -6.228 -6.022 -5.381

>
> c2 <- ((16 * sqrt(3))/(15 * pi))^2
> quantile(plogis(m5d.1$Sol[, 2]/sqrt(1 + c2)))
          0%          25%          50%          75%         100%
0.0003217669 0.1252689677 0.3243001798 0.5006211190 0.8908480698
>
> prob.nz <- plogis(m5d.1$Sol[, 2]/sqrt(1 + c2))
> summary(prob.nz)

Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
      0.328468       0.216151       0.006835       0.032820

2. Quantiles for each variable:

    2.5%      25%      50%      75%    97.5%
0.004825 0.125269 0.324300 0.500621 0.739514

>
> post.prob <- (exp(m5d.1$Sol[,1]))*(1-plogis(m5d.1$Sol[, 2]/sqrt(1 + c2)))
> summary(post.prob)

Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
     1.288e-03      3.989e-04      1.261e-05      3.663e-05

2. Quantiles for each variable:

     2.5%       25%       50%       75%     97.5%
0.0006676 0.0010007 0.0012407 0.0015302 0.0022033

>1.288e-03*150
[1] 0.1932
>
> plot(y=post.prob, x=seq(1,length(post.prob)), type="l")
>
> post.probCap <- (exp(m5d.1$Sol[,1] + m5d.1$Sol[,4]))*(1-plogis(m5d.1$Sol[,
2]/sqrt(1 + c2)))
> summary(post.probCap)

Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
```

```
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
     2.353e-04      1.714e-04      5.420e-06      3.734e-05

2. Quantiles for each variable:

     2.5%       25%       50%       75%     97.5%
2.936e-05 1.098e-04 1.982e-04 3.091e-04 6.968e-04

>
> plot(y=post.probCap, x=seq(1,length(post.probCap)), type="l")
>
> PercReduction.mcmc <- 100*(post.prob-post.probCap)/post.prob
>
> plot(y=PercReduction.mcmc, x=seq(1,length(post.probCap)), type="l", xlab="MCMC
sample")
>
> savePlot(filename = "PercReduction.mcmc.emf", type ="emf")
>
> summary(PercReduction.mcmc)

Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
Sample size per chain = 1000

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
       80.4782        14.8490         0.4696         3.7051

2. Quantiles for each variable:

 2.5%   25%   50%   75% 97.5%
36.45 74.41 83.47 91.49 97.60

>
> quantile(x=PercReduction.mcmc, probs=c(0.025,0.5,0.975))
    2.5%      50%    97.5%
36.45157 83.47225 97.59782
```


m5d.1$Sol[, 3]
m5d.1$Sol[, 4]
m5d.1$Sol[, 1]
m5d.1$Sol[, 2]
Parameter
MCMC sample
0
200
400
600
800
1000
2
0
-2
-4
-6
-8



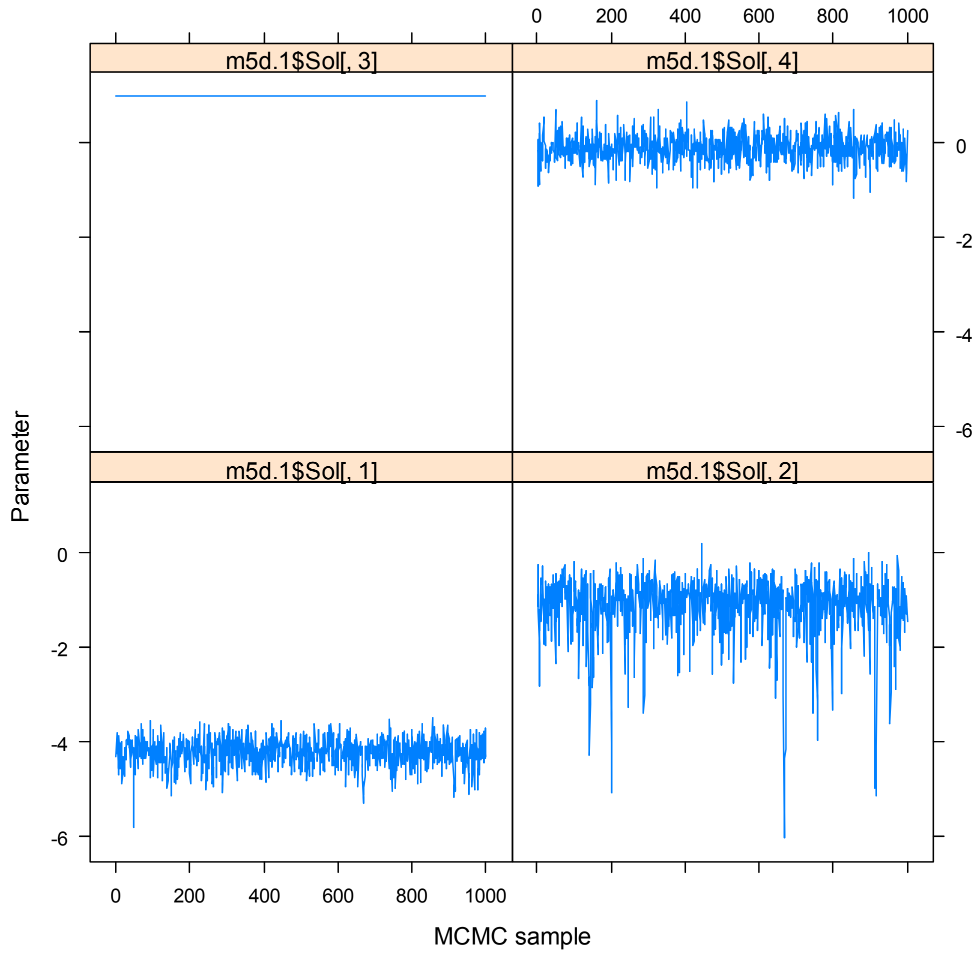
100
80
60
40
20
PercReduction.mcmc
0
200
400
600
800
1000
MCMC sample

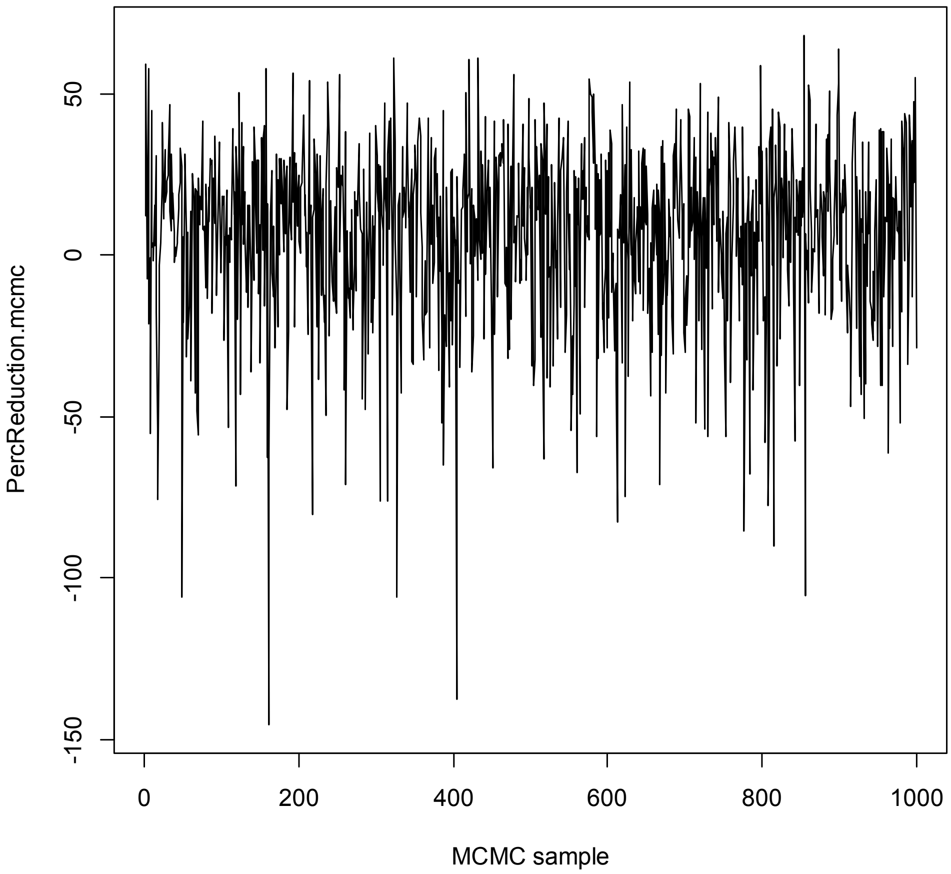


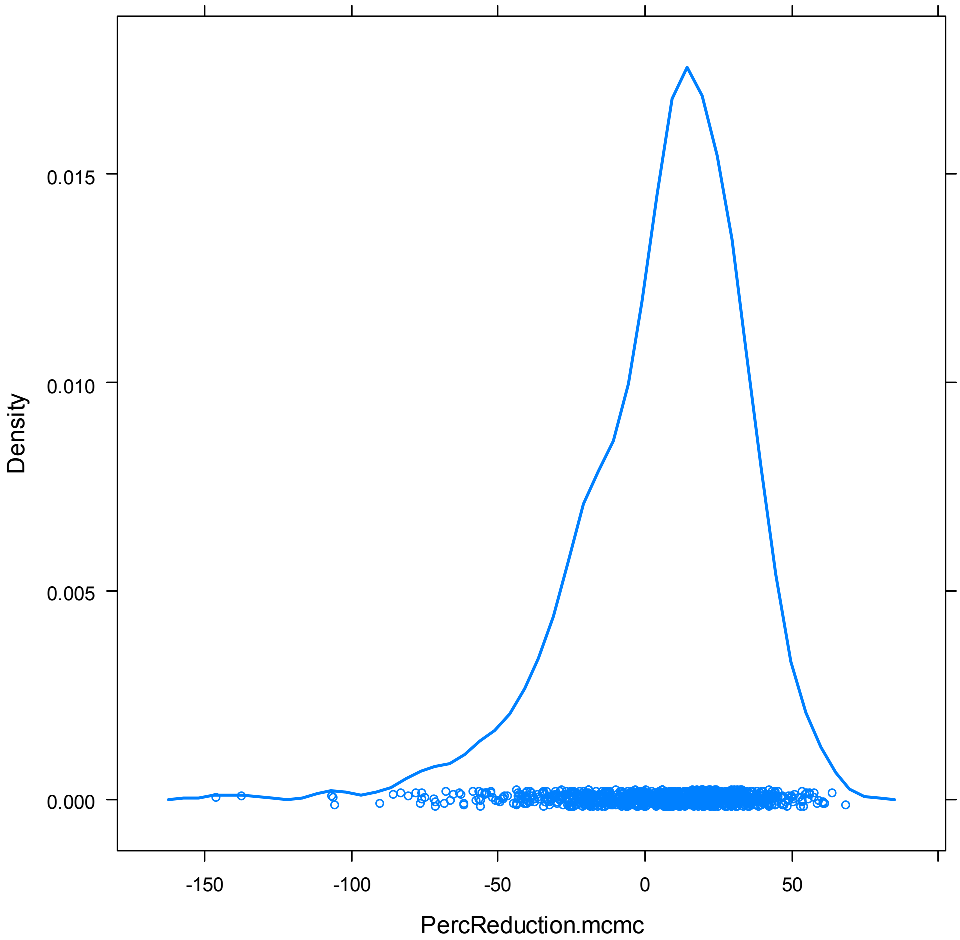

```
>

>  ### Total Commercial Species Catch ###
>
> glmer.01 <- glmer(formula=Total.comm.fish ~ 1 + Treat_f + (1|Pair_f),
offset=Lhooks, data=data, family=poisson)
> summary(glmer.01)
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: poisson  ( log )
Formula: Total.comm.fish ~ 1 + Treat_f + (1 | Pair_f)
   Data: data
 Offset: Lhooks

     AIC      BIC   logLik deviance df.resid
   751.0    759.5   -372.5    745.0      123

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0567 -0.9010 -0.1836  0.5766  2.4908

Random effects:
 Groups Name        Variance Std.Dev.
 Pair_f (Intercept) 0.768    0.8764
Number of obs: 126, groups:  Pair_f, 63

Fixed effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.30381    0.12484 -26.465   <2e-16 ***
Treat_fCap  -0.07204    0.06728  -1.071    0.284
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Correlation of Fixed Effects:
           (Intr)
Treat_fCap -0.260
>
> exp(fixef(glmer.01)[2])
Treat_fCap
 0.9304919
>
> se.teff <- (vcov(glmer.01)[2,2])^0.5
>
> print(c(fixef(glmer.01)[2],se.teff))
 Treat_fCap
-0.07204194  0.06728159
>
> PercReduction <- 100*(1-exp(fixef(glmer.01)[2]))
> sum(fixef(glmer.01))
[1] -3.375854
>
> PercReduction.L1 <- 100*(1-exp(fixef(glmer.01)[2]+2*se.teff))
> PercReduction.L2 <- 100*(1-exp(fixef(glmer.01)[2]-2*se.teff))
>
>
> print(c(PercReduction,PercReduction.L1,PercReduction.L2))
Treat_fCap Treat_fCap Treat_fCap
  6.950813  -6.451707  18.665924


> ### yellowfin tuna catch ###
>
[1] "YFT"
[1] 34 # no Control pairs with > 0 catch
[1] 34 # no Cap pairs with > 0 catch
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  0.000   0.000   1.000   2.262   2.750  30.000
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation)
['glmerMod']
 Family: poisson  ( log )
Formula: resp.var ~ 1 + Treat_f + (1 | Pair_f)
   Data: data
 Offset: Lhooks

     AIC      BIC   logLik deviance df.resid
   456.1    464.6   -225.1    450.1      123

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0012 -0.5335 -0.5101  0.4959  2.3621

Random effects:
 Groups Name        Variance Std.Dev.
 Pair_f (Intercept) 2.068    1.438
Number of obs: 126, groups:  Pair_f, 63

Fixed effects:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -5.079269   0.241152 -21.063   <2e-16 ***
Treat_fCap  -0.007019   0.118468  -0.059    0.953
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
           (Intr)
Treat_fCap -0.245
  Treat_fCap
-0.007018999  0.118468477
 Treat_fCap  Treat_fCap  Treat_fCap
  0.6994424 -25.8496751  21.6477854

Iterations = 200001:699501
Thinning interval = 500
Number of chains = 1
Sample size per chain = 1000
```

```
1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
     1.057e-02      2.434e-03      7.696e-05      7.696e-05

2. Quantiles for each variable:

    2.5%      25%      50%      75%    97.5% 
0.006150 0.008884 0.010483 0.012118 0.015899 


Iterations = 200001:699501
Thinning interval = 500 
Number of chains = 1 
Sample size per chain = 1000 

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
     9.474e-03      2.088e-03      6.604e-05      7.481e-05

2. Quantiles for each variable:

    2.5%      25%      50%      75%    97.5% 
0.005770 0.008033 0.009335 0.010757 0.013896 

NULL

Iterations = 200001:699501
Thinning interval = 500 
Number of chains = 1 
Sample size per chain = 1000 

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

          Mean             SD       Naive SE Time-series SE
        6.3934        27.6577         0.8746         0.8746

2. Quantiles for each variable:

   2.5%     25%     50%     75%   97.5% 
-58.258  -7.893  11.044  24.907  49.216 

     2.5%       50%     97.5% 
-58.25802  11.04394  49.21579 
```


m5d.1$Sol[, 3]
m5d.1$Sol[, 4]
m5d.1$Sol[, 1]
m5d.1$Sol[, 2]
Parameter
MCMC sample
0
200
400
600
800
1000
0
-2
-4
-6


PercReduction.mcmc
50
0
-50
-100
-150
0
200
400
600
800
1000
MCMC sample


0.015
0.010
0.005
0.000
Density
-150
-100
-50
0
50
PercReduction.mcmc